Anticipating Hydroelectric Reservoir Water Levels with Boosted Grey Wolf Optimized Adaptive Random Forest Approach

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The production of hydroelectric power is essential for supplying the world's need for sustainable energy. Sustainable water conservation and reliable electricity generation depend on effective hydroelectric reservoir control. In this work, Boosted Grey Wolf Optimized Adaptive Random Forest (BGWO-ARF), a unique method for forecasting water levels in hydroelectric reservoirs, is presented. To improve forecasting accuracy, the suggested model combines the best optimization qualities of the GWO methodology with the adaptive abilities of the RF algorithm. Integrating hydrological factors, weather conditions and historical reservoir volume information, the BGWO-ARF represents the intricate dynamics of changes in water level. Numerous tests were carried out using India's hydroelectric reservoir dataset to assess the effectiveness of suggested strategy, which revealed greater prediction accuracy compared with previous techniques. To examine the efficiency of the proposed technique compared to standard processes, the suggested method achieves RMSE, MAE and RAE. The findings show that the BGWO-ARF method improves the accuracy and dependability of water level forecasts, which helps decision makers make well-informed choices for best possible reservoir upkeep and operation. This study gives important insights into sustainable use of water resources in the environment of hydroelectricity production and advances predictive models in hydrology.

Keywords: Hydroelectric power, water level, reservoir control, Sustainable conservation, Boosted Grey Wolf Optimized Adaptive Random Forest (BGWO-ARF).

1. Introduction

The water levels in hydroelectric reservoirs are a significant component in the efficient and environmentally acceptable production of electricity. By collecting and retaining water for eventual consumption in electricity generation, these reservoirs constructed by damming rivers perform a significant importance in hydroelectric power plants [1]. To balance electrical needs, reduce the possibility of flooding and support a variety of downstream environmental structures, it is essential to evaluate and manage ideal water levels in these reservoirs [2]. Hydroelectric reservoirs provide effective electricity production by controlling water levels, ensuring a steady supply of renewable energy with less environmental implications than conventional power plants [3]. Water resource sustainability and regional growth are assisted when water levels can be managed for irrigation, residential water supply and commercial consumption.

Hydroelectric reservoir's water levels perform an essential significance in maintaining sustainability in electricity development and water resources administration [4]. The use of machine learning (ML) techniques indicates possibilities as a means to anticipate prospective reservoir water levels, which would improve management preparation and decision-making [5]. ML algorithms can forecast water levels by employing previous information, climatic structure as well as ecosystem characteristics, enabling adaptive administration of flood administration, electricity generation and environmental conservation [6]. This revolutionary technique enables a water-energy connection that is economically efficient and adaptable while simplifying the optimization of hydroelectric power generation and reducing the challenges of water scarcity and flooding. The use of machine learning to analyze water levels in hydroelectric reservoirs has the potential to transform water management and achieve our energy requirements in the long term [7, 8].

Estimates of reservoir water levels can be complicated by considerations such as a lack of sufficient data, difficulties in including extensive environmental characteristics and limitations in adaptation to evolving hydrological circumstances. By applying current optimizing methods, this model will generate accurate forecasts, assuring effective resource administration and ecological electricity production. In development, reservoirs can be managed effectively, leading to improved water resource planning and higher general hydroelectric energy production.

The additional divisions of this article are as follows: Introduces related works in part 2, part 3 discusses the methodology, part 4 results and discussion and part 5 concludes the paper.

2. Related works

According to the author of, [9] presented a features-reducing method such as principal component analysis and feature grouping techniques with ML regression methods, including artificial neural networks (ANN) and support vector machines (SVM). They demonstrate that ML regression algorithms might estimate hydroelectric production. The study [10] presented a deep learning-based technique for predicting reservoir outflow and “recurrent neural network (RNN), long short-term memory (LSTM) and gated recurrent unit (GRU)” to develop predictive algorithms for the reservoir’s outflow. The findings demonstrate that the three developed algorithms acquire the reservoir operation regulations from past operating data and provide an operating strategy for the reservoir's flood management and power generation. Article [11] developed an ANN model that was dependent on past hydrological data, comprising stream flow, dam updates and reservoir storage levels at the beginning and end of the year. This ANN was the utility of provided data on water losses, ultimate storage and water level variations for improved reservoir performance.

To presented an ANN on the basis of stream flow predictions and the reservoir simulation. Two multistep-ahead prediction techniques, identified as Close-Loop Prediction (CLP) [12] and Open-Loop Prediction (OLP), were used to forecast streamflow. Subsequently associated with the most potential streamflow predictions constructed with the CLP technique over the summer, the reservoir modeling demonstrated significant efficiency for reservoir level projections. The developed a deep learning model based on the LSTM (13) network to predict the regular water condition of Dongting Lake. The findings of the experiment, the water level in Dongting Lake simplified consistently during the months of September as well as November, Three Gorges Dam (TGD) was impounded and improved between dry seasons, when TGD was supplemented. The developed a deep reinforcement learning (DRL) [14] architecture that was built based on a specifically established information samples structure and a deep Q-network (DQN). The suggested DRL models for annual hydropower production and systems dependability outperform the comparative simulations. According to the author of, [15] presented a new framework based on four different types of delicate structures: “support vector regression (SVR), adaptive neuro-fuzzy inference system (ANFIS), ANN and radial basis function neural network (RBFNN)."The results of employing the suggested method demonstrate that the supervised (hybrid) models perform better than delicate models to minimize the inaccuracy in water level predictions.

Author [16] evaluated a multiple linear regression (MLR), ANN, extreme learning machine (ELM) and SVM performed when attempting to predict the rule for operating a hydroelectric reservoir. The standard SGM method was used as a reference standard for the comparison. The experiments demonstrate that the three AI algorithms tested (ANN, SVM and ELM) outperformed the traditional MLR and scheduled graph approach. To presented a Bayesian Deep Learning technique [17] that required considering the variability of the model's parameters and the probability of the incoming data. Standards for operating reservoirs in actual moments were essential, with the immediate reservoir condition and anticipated inflows constituting the primary considerations. The experimental findings demonstrate that the suggested Bayesian deep learning method was more effective at maximizing hydropower production than the standard technique. To employed the Smart Climate Hydropower Tool (SCHT) [18], a revolutionary, cloud-based interactive technology that reflect data-driven, machine learning-based algorithms for river discharge forecasting. Implementing SCHT generated findings that supported the employment of ML algorithms with complicated and recurrent architecture for generating an effective periodic dynamical prediction of the total river discharge input across the application investigations.

3. Methodology

In this study, we present Boosted Grey Wolf Optimized Adaptive Random Forest (BGWO-ARF), a novel technique for predicting water levels in hydroelectric reservoirs. The dataset was developed by utilizing five years of collecting information on the water level to calculate the flow rate and water level at "Yedgaon Dam", a collection with its individual output and reservoir.

3.1 Dataset

The significance of the investigation is to develop forecasts for the overall water level and regular outflow estimates at Yedgaon. The five reservoirs that constitute together the Kukadi integrated system were located in the Sahyadri hill range in the Western Ghats of Maharashtra, which provides the experimental area. The examination comprises the greater administrative area in the Pune, Solapur and Ahmednagar administrations. The Google image of the Kukadi complex is provided in Figure 1 below to provide context for the location under examination.

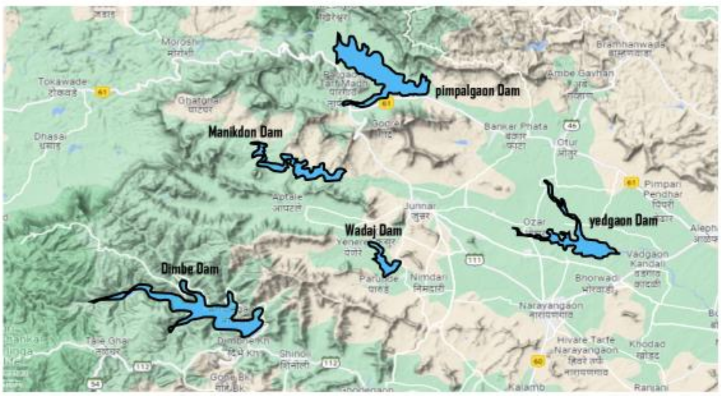

Figure 1: Google image of the Kukadi complex [Source: Google map]

The complete Kukadi development has a potential irrigable management surface of 156278 Ha. Daily distribution measurements and complete water level statistics for the Kukadi irrigation project's Manikdoh, Dimbhe, Wadaj, Pimplgaojoge and Yedgaon were collected from the hydrology administration (Kukadi Hydrology Section No.1, Narayangaon) between June 1, 2015 and August 31, 2019. Each station has access to daily flow measurements from 592 inspections and complete water level statistics from 1548 occurrences. The quantitative characteristics of the regular outflow are shown in Table 1 and complete water level empirical characteristics are displayed in Table 2 [21].

Table 1: Characteristics of regular outflow at each investigation site [21]

Stations	Manikdoh	Wadaj	Dimbhe	Pimpalgaojoge	Yedgaon
Average value	276	69	480	258	145
Standard Deviation	456.30	97.77	192.40	452.09	881.01
Range of parameters	0 to 1250	0 to 364	0 to 650	0 to 1450	138 to 11966

Table 2: Complete water level statistics analytical characteristics for the locations under assessment [21]

Stations	Wadaj	Yedgaon	Pimpalgaojoge	Manikdoh	Dimbhe
Range of parameters	699.69 to 717.53	634.22 to 641	673.01 to 686.62	681.75 to 709.99	682.55 to 719.15
Standard Deviation	4.43	8.42	3.31	8.42	11.83
Average value	712.57	694.95	682.56	694.95	705.30

3.2 Boosted Grey Wolf Optimized Adaptive Random Forest Approach

Economically dependable electricity generation can be attained through the combination of various methods of operation, which allow for optimized reservoir management and power generation. Together, these improvements in reservoir water level prediction and optimization of hydroelectric authority and resource management constitute a significant step forward in the field.

3.2.1 Boosted Grey Wolf Optimization

The entirety reduction techniques involve the difficult problem of determining the global optimum. Approximation to the global optimum can be considered as happening in two distinct but related processes in population-based optimization techniques. It's important to get people distributed across the complete searched environment in the initial phases of optimization. Instead of gathering towards optimal solutions, they should spread outward to investigate the possibilities. Individuals must use the knowledge they have gained to converge on the global optimum in the subsequent phases. By establishing a compromise between these two phases, we can converge to the global optimum using GWO after fine-tuning the parameters A and A. Local optimum avoiding is assisted by various updates to individual-based algorithms, although evidence demonstrates that population-based algorithms accomplish better when presented with this constraint. The optimization procedure is separated into two competitive achievements in population-based algorithms, exploring and exploiting. Exploring generates unpredictable and unexpected adjustments in potential responses. The method translates into enhanced response variability and comprehensive spectrum investigation. Exploitation, on the alternative moment, attempts to enhance the integrity of solutions by conducting local investigations proximal to the potential solutions identified during the inspection. Prospective alternatives are required to make reduced extreme modifications and conduct localized searches in subsequent period. Exploring and extraction are competing objectives and encouraging one serves to undermine the individuals. When these two objectives are coordinated, population-based algorithms can produce an efficient simulation of the global optimal. In one sense, an algorithm can't reliably approximate the global optimum if it explores the examined region. Relying on simple exploiting contributes to prevent in the progress of local optimums and, once again, a poor approximation of the optimum. The GWO shift between exploring and extraction is controlled by the varying values of α and$B$. They expend part of the repetitions exploring ($|B| \geq 1$)and the remaining part exploiting($|B| < 1$). As the discovery space expands further, the possibility of remaining at a local optimum decreases. One way to increase the rate of exploration is by substituting quadratic measures with exponential measures to decrease over a series of iterations. Considering excessive unpredictability, frequent investigation is uncertain to generate significant optimization consequences. But excessive exploitation is associated with inadequate opportunity. Thus, there should be a middle ground between discovery and exploitation. Using the following modified equation, the amount of a GWO impacts from 2 to 0.

$$b = 2\left(1 - \frac{s}{S}\right) \tag{1}$$

Maximum repetitions, denoted by S and the present repetition, denoted by$t$, are conceivable. For the gradual decrease of BGWO, they employ an exponential equation.

$$b = 2\left(1 - \frac{s^2}{S^2}\right) \tag{2}$$

The percentage of iterations in investigation against extraction utilizing this exponential degradation equation is defined at 80% and 40%, correspondingly.

3.2.2 Adaptive Random Forest

Numerous investigations demonstrate that the random forest algorithm provides superior categorization efficiency, noise acceptance and resistance to over fitting. To enhance the reliability of algorithm classification, the ARF algorithm described in the investigation utilizes an adaptive evaluation procedure of characteristics to fine-tune the method of decision tree node separation. Because of these variations in features, decision trees are generated using distinct component splitting techniques on the identical data set might resemble very different from one another. The results indicate that random forest categorization effectiveness differs. It is suggested that the decision tree determines the appropriate characteristic to separate the nodes and divide the node-separating technique into a linear combination to generate a new separating rule, which is implemented in the node characteristic selection and separation. The node-separating technique displays the distribution coefficient and informational benefit by separating the dataset C dependent on characteristic a.

$$Gain\,(C,b) = Ent(C) - \sum_{u=1}^{U} \frac{|C^u|}{|C|} Ent(C^u) \tag{3}$$

$$Gini(C,b) = \sum_{u=1}^{U} \frac{|C^u|}{C} Gini(C^u) \tag{4}$$

Where C^v signifies that examinations in the C with a frequency of u on a characteristic are contained in the b^u segment node

$$Ent(C) = -\sum_{l=1}^{|z|} o_l log_2 o_l \tag{5}$$

$$Gini(C) = \sum_{l=1}^{|z|} \sum_{l' \neq l} olol' = 1 - \sum_{l=1}^{|z|} ol^2 \tag{6}$$

The combined node separating calculation and responsive component selection procedure appear such that because the method of node separating is to desire for the enhanced purity of the data set between separation.

$$G = \min_{\propto,\beta \in Q} E\{C, b\} = \alpha Gini(C, b) - \beta Gain(C, b) \begin{cases} \propto + \beta = 1 \\ 0 \leq \alpha, \beta \leq 1 \end{cases} \quad (7)$$

$\propto, \beta$ are indicating the attribute-splitting weighted component. G Has insignificant importance. To obtain the most effective settings for the combination, an adaptive procedure for parameter evaluation is employed.

The experiment evaluates the performance based on the classification error rate and the consistency frequency. Sample C rate of misclassification is calculated using Equation (8).

$$F(e; C) = \frac{1}{n} \sum_{j=1}^{n} \mathrm{II}\big(e\big(w_j\big) \neq z_j\big) \quad (8)$$

The frequency of efficiency is calculated using Equation (9).

$$acc(e; C) \frac{1}{n} \sum_{i=1}^{n} \mathrm{II}\,\big(e\big(w_j\big) = z_j\big) = 1 - F(e; C) \quad (9)$$

3.2.3 Boosted Grey Wolf Optimized Adaptive Random Forest (BGWO-ARF)

To anticipate water levels in hydroelectric reservoirs, an innovative combination of the boosted Grey Wolf Optimization (BGWO) method with an enhanced adaptive Random Forest (ARF) model is developed. Integrating the exceptional by exploring and exploiting characteristics of BGWO with the substantial estimation capacity of RF, this particular technique promises to overcome the constraints of standard techniques and present more exact and dependable predictions of water levels. To explore the response of environment and determine the optimum parameters for the RF model, the BGWO provides sophisticated exploration qualities motivated by the pursuing technique of grey wolves. Further, by utilizing cutting-edge feature selection approaches and fine-tuned hyper parameter improvement, the adaptive RF algorithm improves the model's predictive efficiency, enabling it to recognize intricate connections in complicated hydrological information. By combining the characteristics of BGWO and RF, such combination architecture is anticipated to improve beyond prior approaches for predicting water levels in hydroelectric reservoirs. Algorithm 1 shows the pseudocode for (BGWO-ARF).

Algorithm 1: Boosted Grey Wolf Optimized Adaptive Random Forest (BGWO-ARF)

```
import numpy as np
import pandas as pd
from sklearn.ensemble import RandomForestRegressor
from greywolfoptimizer import GreyWolfOptimizer
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.ensemble import AdaBoostRegressor
data = pd.read_csv('hydroelectric_data.csv')
def gw_optimization(X_train, y_train):
```

$def\ objective\_function(hyperparameters)$:

$$model = RandomForestRegressor(n\_estimators = int(hyperparameters[0]), max_{depth} = int(hyperparameters[1]), min\_samples\_split = int(hyperparameters[2]), min\_samples\_leaf = int(hyperparameters[3]), random\_state = 42)$$

$model.fit(X\_train, y\_train)$

$y\_pred = model.predict(X\_test)$

$return\ mean\_squared\_error(y\_test, y\_pred)$

$gwo = GreyWolfOptimizer(objective\_function, \{'n\_estimators': (50, 200), 'max\_depth': (10, 50), '$

$return\ gwo.optimize()$

$best\_hyperparameters = gw\_optimization(X\_train, y\_train)$

$ada\_rf = AdaBoostRegressor(RandomForestRegressor(n\_estimators = int(best\_hyperparameters['n\_estimators']), max\_depth = int(best\_hyperparameters['max\_depth']), min\_samples\_split = int(best\_hyperparameters['min\_samples\_split']), min\_samples\_leaf = int(best\_hyperparameters['min\_samples\_leaf']), random\_state = 42), n\_estimators = 50, random\_state = 42)$

$ada\_rf.fit(X\_train, y\_train)$

$y\_pred = ada\_rf.predict(X\_test)$

$mse = mean\_squared\_error(y\_test, y\_pred)$

$print(f"Mean\ Squared\ Error: \{mse\}")$

4. Result and discussion

The proposed approach has been implemented employing the Python 3.11 platform, Tensor Flow version 1.14.0 and Anaconda version 2019.07. The laptop is equipped with the OS-10, with a Ryzen 5 processor and 6 GB of RAM. The performance of the proposed method is analyzed in terms of various parameters, including RMSE, MAE and RAE to assess the effectiveness of the proposed technique in comparison to existing approaches. We employ parameters like “Support Vector Machine (SVM) [19], “Multi-layer Perceptron” (MLP), “Gaussian Process Regression” (GPR) [19], Neural Network (NN) [20] and Decision Forest Regression (DFR) [20].

Figure 2 illustrates the BGWO-IRF estimate and the particular frequency for each experiment sample. Considering the regularity of the dataset examples over time, it is apparent that the data structure in this circumstance is flatter. The improved findings in both error measures analyzed and suggest that the structural consistency in the dataset has enabled the algorithm to produce a superior forecast. The BGWO-IRF outcome resembles the actual environment data, with a few instances demonstrating unexpected abnormalities due to dramatic fluctuations. Remember that this fundamental element of the dataset has been compensated for the BGWO-IRF.

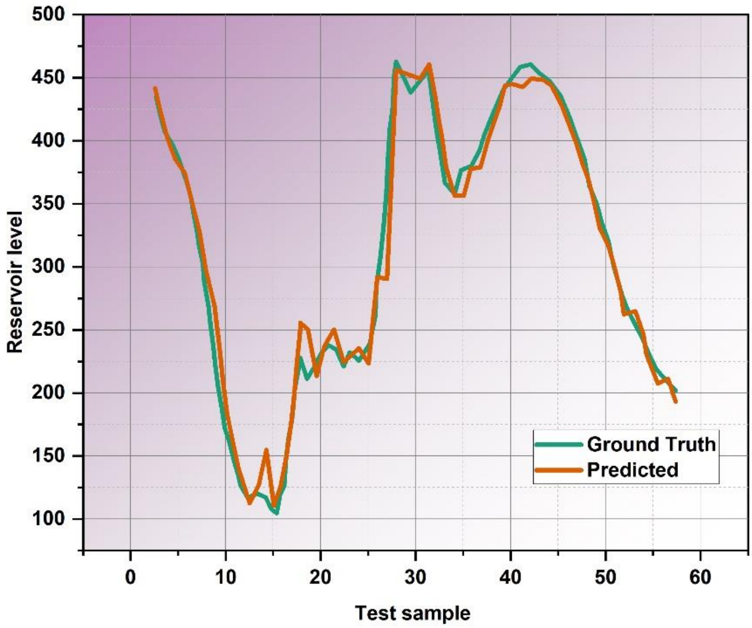

Figure 2: BGWO-IRF vs. Ground truth [Source: Author]

Root Mean Square Error (RMSE) evaluates the intensity of the prediction assumed by determining the square root of the mean squared deviations between forecasted and measured water levels. It calculates prediction errors. RMSE comparison is displayed in Figure 3 and Table 3. In comparison, the performance of the existing technique, SVM, MLP and GPR, was 22.56, 23.42 and 24.42, while our suggested solution BGWO-ARF had 20.60. The outcomes demonstrate that our suggested approach has a lower RMSE in comparison with the existing methods.

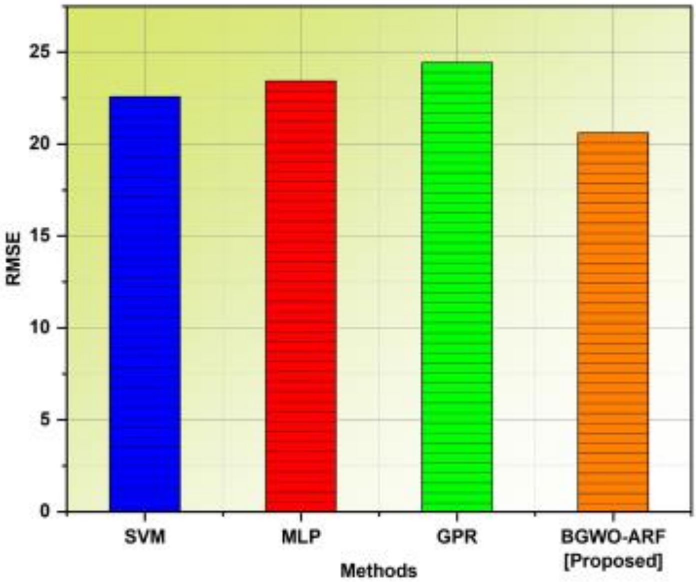

Figure 3: Output of RMSE

Table 3: Comparison of RMSE

Methods	**RMSE**
SVM	22.56
MLP	23.42
GPR	24.43
BGWO-IRF [Proposed]	20.6

Mean Absolute Error (MAE) enables a simplistic evaluation of forecast performance by determining the averaged percentage variances between anticipated and observed water levels in hydroelectric reservoirs. Figure 4 and Table 4 show the MAE comparison and the performance of the existing technique, SVM, MLP, GPR and NN, was 16.46, 17.38 and 19.28, while our proposed method BGWO-ARF had 14.20. The results show that, comparing to the existing approach, our proposed technique has a lower MAE.

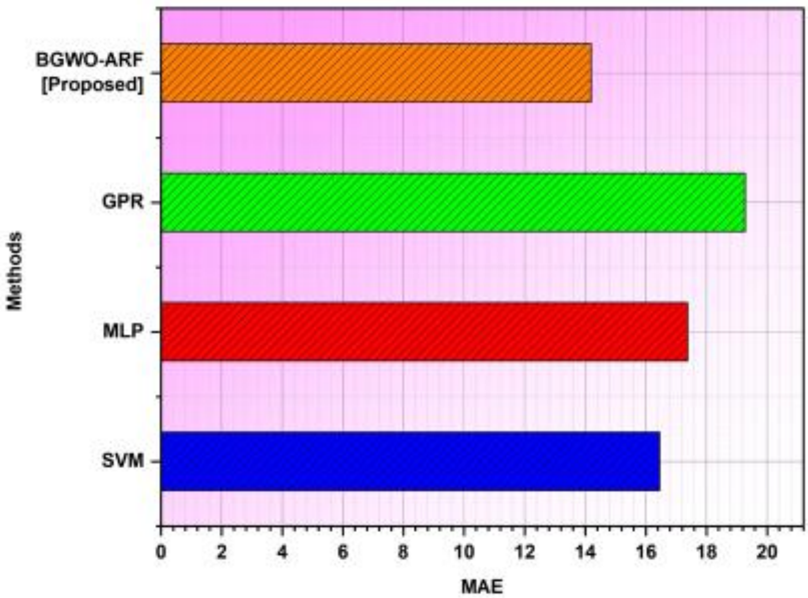

Figure 4: Output of MAE

Table 4: Comparison of MAE

Methods	MAE
SVM	16.46
MLP	17.38
GPR	19.28
BGWO-IRF [Proposed]	14.2

Reservoir Area Estimation (RAE) technique hydropower reservoir water levels are evaluated and reservoir surface areas are calculated, which are essential for efficient substance administration, flood management, hydropower scheduling and ultimately, for maintaining a healthy ecological as well as industrial balance. Figure 5 and Table 5 show the RAE comparison. The performance of the existing technique NN and DPR was 0.168 and 0.251, while our proposed method BGWO-AARF had 0.098. The results demonstrate that our proposed strategy reduces the MAE when compared to the existing methodology.

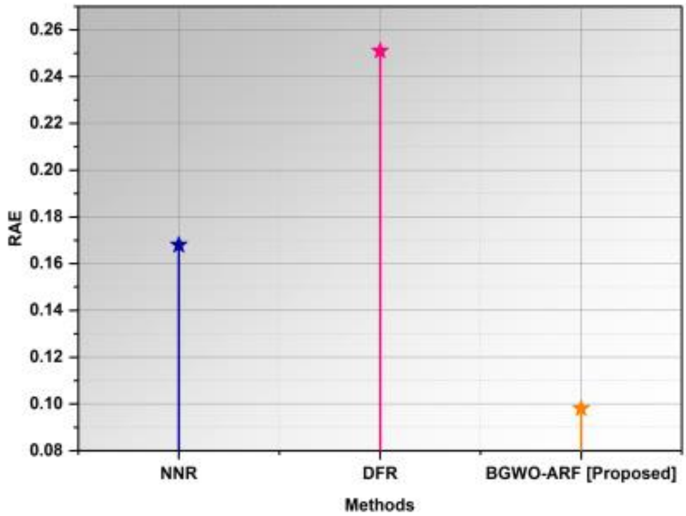

Figure 5: Output of RAE

Table 5: Comparison of RAE

Methods	RAE
NNR	0.168
DFR	0.251
BGWO-IRF [Proposed]	0.098

5. Conclusion

Hydroelectric power production is essential for satisfying the global requirement for environmental energy, effective water management and dependable electrical transmission dependent on the efficient management of hydroelectric reservoirs. This research proposes the Boosted Grey Wolf Optimized Adaptive Random Forest (BGWO-ARF) model that integrates the enhancement features of the GWO technique with the responsive characteristics of the RF algorithm to produce accurate water level forecasts. The BGWO-ARF model demonstrates the complicated processes of water level variations by incorporating a wide range of hydrological parameters, atmospheric circumstances and historical reservoir measurements. The approach's RMSE (20.60), MAE (14.20) and RAE (0.098) on India's hydroelectric reservoir collection demonstrate that it achieves better forecasting efficiency compared to existing methodologies. The findings indicate a substantial improvement in forecasting precision and performance, presenting decision-makers with the information they require to make educated selections about reservoir management and execution. This investigation improves the area of hydrology by contributing to the development of more effective forecasting systems for the management of water resources in the environment of hydroelectricity generation. In order to predict the level of water in hydroelectric reservoirs, standard techniques employ simplistic assumptions that cannot represent the intricate interaction of elements impacting water levels. These techniques can have difficulty integrating several categories of information, especially hydrological characteristics and historical reservoir statistics. Furthermore, investigating the feasibility of combining different measurement techniques and utilizing prediction intelligence for improved reservoir management maintains the possibility for future advancements.

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